AnalogiLead: Improving Selection of Analogical Inspirations with Chunking and Recombination

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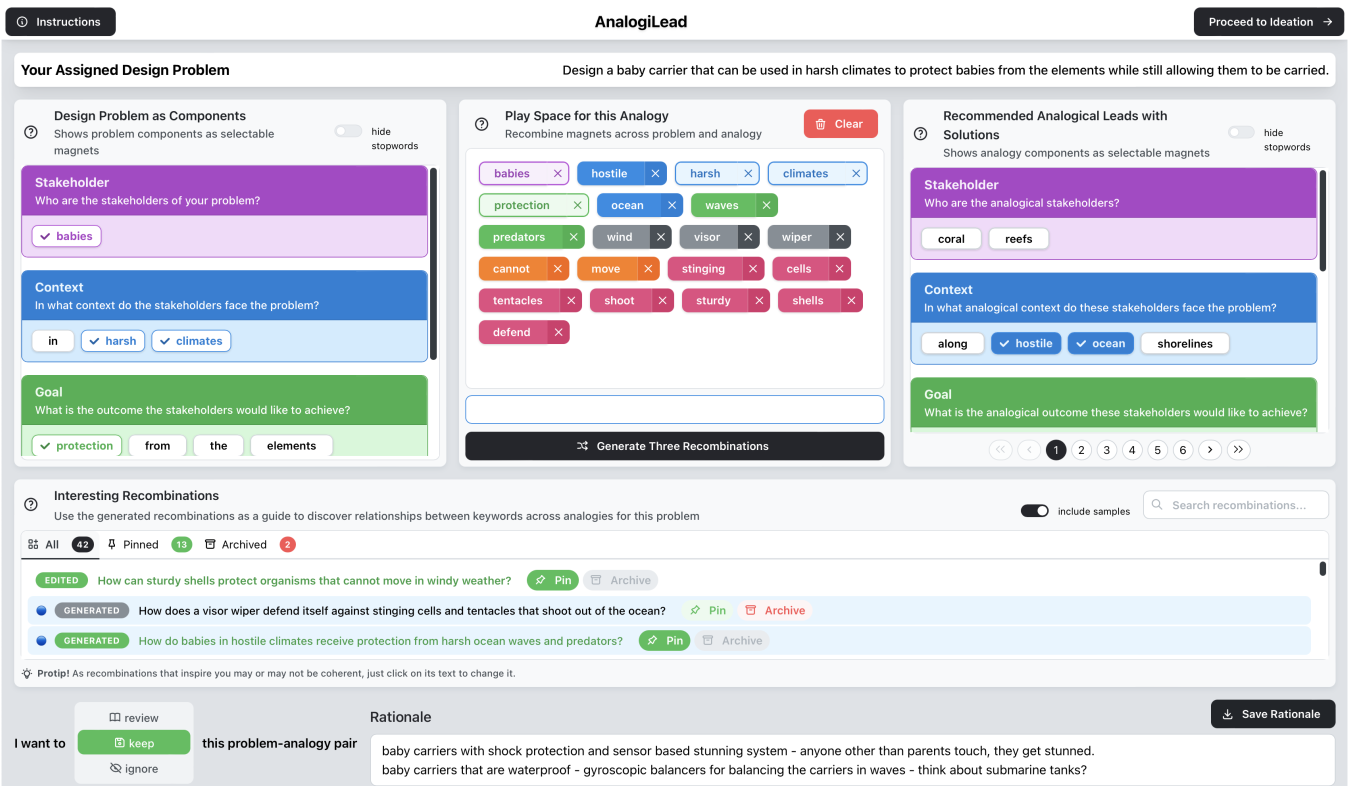

Figure 1: Our proposed System. The interface is split into three rows. In the first row, the users select *magnets* (2.1) from the Problem and their corresponding Analogy, mixing them or adding their own in the *Playspace* (2.2) to generate insightful questions/*recombinations* (2.3) to facilitate divergent thinking and as a result, aid in recognition of beneficial analogies.

ABSTRACT

Analogical reasoning, a process that integrates potential leads across domains and disciplines, has been proven to contribute to breakthrough innovations. Selecting the right analogical leads is crucial, as it determines the quality and effectiveness of the generated ideas. However, identifying relevant analogical leads can be challenging and may be missed due to premature rejection or design fixation. To address this problem, our system, *"AnalogiLead"*, draws on the cognitive mechanisms of chunking and recombination as a medium of interaction for selecting beneficial analogies. Users interact with meaningful chunks or segments from a design problem and analogy, represented as interactive tiles called *"magnets"*, and evaluate the analogies by recombining the *"magnets"* into brainstorming questions. These mechanisms are designed to foster playful and divergent exploration of analogical leads (vs. restrictive, relevance-based screening), to reduce premature rejection of analogical leads and foster more analogical innovations.

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CCS CONCEPTS

• **Human-centered computing** → **Graphical user interfaces**; **Web-based interaction**; **User interface design**; • **Computing methodologies** → *Machine learning*;

KEYWORDS

Creativity Support, Machine Learning, User Interface Design, Information Seeking & Search

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1 INTRODUCTION

Analogical reasoning has been recognized as a powerful tool for generating breakthrough innovations. Analogical thinking involves drawing connections between seemingly disparate domains to generate new ideas and approaches by identifying structural similarities [11, 13, 24, 25]. Far analogies, in particular, have been instrumental in some of the most significant scientific and technological breakthroughs throughout history [6, 12, 21, 35, 41].

However, selecting relevant analogical leads can be challenging due to the preference of memory retrieval for near, within-domain analogies that share object attributes [14, 15, 19, 28]. Furthermore, analogical processing can be demanding on cognitive resources, often exhausting working memory, especially when multiple relations need to be processed at once [18]. This can sometimes result in sub-optimal outcomes, as seen in the development of the first microwave oven, which was inspired by the analogy between radar and cooking but took several years to develop into a viable product, due to an improper understanding of users needs [10].

Existing approaches to analogical processing have attempted to address these challenges through instruction [16, 30, 37] or non-overgeneralized [39] abstract representations of problems and analogical examples [27, 42]. Computational models and systems have also been proposed to facilitate this process through various techniques of abstraction and representation [5, 9, 11, 27, 33]. However, mere exposure to beneficial analogical leads alone is not enough to ensure their adoption in problem-solving [23]: factors such as expertise [2, 36], presence of usable anchors [3], optimal representations [7, 8, 11, 17], and diversity of solutions [27] can affect the premature rejection of potential leads, leading to design fixation [1, 26, 32].

Fully-automated analogical search engines such as SOLVENT [5] and ProbMap[34] have proposed breaking down a problem into functional components such as *Stakeholders*, *Purpose* and *Mechanism* to facilitate computational retrieval of new analogical leads. Given prior research on the creativity benefits of interacting with ideas in terms of their **conceptual "chunks"** [29, 43], we hypothesize that these conceptual "chunks" may also be beneficial for structuring interactions with existing analogical leads in a way that supports creative exploration and (re)interpretation (and thus less premature rejection) of analogical leads. In addition, aligning non-identical relational predicates has been suggested to be facilitated by re-representation [14, 31], which can assist in identifying and retrieving relevant analogies in complex systems. Earlier studies conducted in learning environments have explored questions as a possible mechanism to facilitate this process of re-representation and **recombination**; attempting to facilitate the creation of new linkages between unlinked or previously linked components targeting specific applications [20]. According to Herring et al. [22], designers were found to utilize examples by re-appropriating and recombining solution components to generate novel ideas. Additionally, studies conducted in learning environments have found that questions play a vital role in promoting creative thinking. In particular, open-ended questions were found to greatly increase divergence in thinking [40]. A recent study [38] that proposed a system to semi-automatically generate external stimuli in the form of questions found that individuals, who were exposed to these generated questions produced better and more versatile ideas that those who were not. Our approach uses Large Language Models [4] to make this process easier and more accessible.

Building on these insights, we designed a new system that leverages chunking and recombination mechanisms to support the recognition and adoption of far-domain analogies, facilitating their transfer across domains, and mitigating design fixation. By addressing these challenges, our proposed system aims to improve the effectiveness of analogical reasoning in generating breakthrough innovations.

2 THE ANALOGILEAD SYSTEM

The AnalogiLead System is designed to foster creative idea generation and problem-solving through its three key sections: *Magnets*, *Playspace*, and *Recombinations*.

2.1 Magnets

The Magnets in the AnalogiLead System are carefully curated and pre-defined sentence fragments or phrases that represent common functional constraints or attributes related to the problem domain. Expanding upon prior studies, we break down the problem into four components, namely:

Stakeholder. This functional constraint highlights the beneficiaries who will be affected by the assigned design problem.

Context. This functional constraint highlights the context in which the aforementioned stakeholders face the assigned design problem.

Goal. This functional constraint highlights the goal that the stakeholders need to achieve to solve the assigned design problem.

Obstacle. This functional constraint highlights an obstacle that hinders the stakeholders from achieving their goal for the assigned design problem.

Alongside these functional constraints, the recommended analogical leads add an additional constraint to highlight the solution:

Solution. This functional constraint highlights the solution proposed to solve the goal of the recommended analogical lead for the given design problem.

These Magnets are designed to be flexible and versatile, allowing users to select and combine them in various ways to create prompts for idea generation. The Magnets serve as building blocks or "chunks" of ideas that can be easily manipulated and rearranged to construct meaningful questions via. the Playspace.

2.2 Playspace

The Playspace is where users can experiment with the selected Magnets to create questions. The system uses Generative Pretrained Models (GPT) to automatically generate a wide range of questions by recombining the selected Magnets in real-time. The generated questions serve as prompts for the user to explore different angles and perspectives on the problem at hand, sparking creative thinking and encouraging divergent ideas. The user can iterate and experiment with different combinations of Magnets in the Playspace to generate a multitude of questions that prompt unique insights and solutions, promoting divergent thinking.

2.3 Recombinations

The Recombinations section of the AnalogiLead System provides users with the option to further customize and refine the generated questions. Users can edit and modify the questions to better align with their thought process, specific problem domain, or desired outcome. This customization capability allows users to fine-tune the prompts to their specific needs, ensuring that the generated questions are relevant, meaningful, and tailored to their unique requirements. The Recombinations section empowers users with creative control, enabling them to craft prompts that are aligned with their creative goals and objectives.

The combination of Magnets, Playspace, and Recombinations in the AnalogiLead System creates a dynamic and iterative process for idea generation and problem-solving, ultimately facilitating in selecting the most beneficial analogies for a given problem. The system leverages the power of Generative Pretrained Models to generate a wide range of prompts, while providing users with the flexibility to customize and refine the prompts to suit their creative process. This human-in-the-loop approach fosters exploration of diverse ideas and encourages unique approaches to problem-solving, making the AnalogiLead System a powerful tool for stimulating creativity and improving selection of analogical inspirations while preventing possibilities for premature rejection and design fixation.

3 TECHNICAL OVERVIEW

3.1 Prompt Engineering

Prompt:

> By combining the following list of words together, generate [n] meaningful questions with insightful relationships: [word1, word2, ..., wordN]
> Output:
> 1.

The interface uses the OpenAI language model `text-davinci-002` for generating recombinations in a zero-shot learning context. Longer prompts including functional constraints resulted in confusing outputs, so the prompt structure was simplified. Descriptive words like *"insightful"* and *"meaningful"* were added to prioritize recombinations. The parameters for generating responses, such as temperature, frequency penalty, and presence penalty, were adjusted to balance creativity and coherence. A temperature value of 0.75 was used for moderate randomness, and frequency penalty and presence penalty values of 0.5 and 0.25, respectively, were used to encourage unique and diverse responses without overly strict penalties.

3.2 Software Implementation

This interface is developed using the React Framework in JavaScript, which is a popular choice for building user interfaces. React provides a set of reusable primitives that can be used to create interactive web applications. React Hooks are used to simplify the code making it easier to manage and reuse code across components. To store data, the system uses Firestore Backend as a service, which is a cloud-based NoSQL database offered by Google. Firestore provides scalable storage and real-time synchronization for mobile, web, and server applications.

4 DEMONSTRATION

For the purposes of this demonstration, a preset design problem will be presented, each with six corresponding handpicked analogies. Three analogies would be from a domain with varying degrees of closeness to the problem while the remaining would be from a far, yet structurally related domain. The demo will invite engagement from the participants by giving them the freedom to play around with the magnets of the problem and analogies, mix them or add their own magnets to the Playspace to generate recombinations. We also hope to expand the demo, to accommodate for users problems instead of preset-ones if possible, to promote greater engagement with the audience. Since the proposed system is a Web-interface and given the virtual nature of the event, there is no additional requirement needed for setup.

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